

An AI-enhanced hybrid project management model: a comparative evaluation using the weighted sum model

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ABSTRACT

Projects today face increasing complexity, uncertainty, and regulatory constraints that often limit the effectiveness of traditional and strictly Agile project management (PM) methods. Current hybrid methods remain largely theoretical and lack integrated decision-support tools that combine predictive analytics with transparent multi-criteria evaluation. To address this gap, this paper presents an artificial intelligence (AI)-enhanced hybrid project management model (AI-HPMM) that combines AI functionalities with the weighted sum model (WSM) to support adaptive, data-driven, and transparent decision-making. A systematic literature review was conducted according to preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines (2019–2025), identifying ten success factors aligned with project management body of knowledge (PMBOK) domains. These factors were weighted using WSM to compare Agile, Waterfall, and AI-enhanced hybrid methods. AI-HPMM achieved the highest WSM score (9.96/10), outperforming Agile (7.66/10) and Waterfall (7.90/10). The reviewed literature also reports a 15% reduction in schedule deviations, a 12–20% improvement in resource efficiency, and a 25–30% increase in decision-making speed. Overall, the proposed model improves adaptability, transparency, and responsiveness in complex and dynamic project environments.

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1. INTRODUCTION

Nowadays, projects have to deal with complexity and uncertainty that have increased exponentially. Companies are facing unstable markets, changing stakeholder requirements, and tighter standard regulations. It is under such circumstances that the traditional project management (PM) methods, although proven to be effective in stable environments, usually fail to deliver satisfactory results [1]. Additionally, these limitations have influenced the extent to which the hybrid project management (HPM) approach is adopted, which blends predictive planning with flexible practices to achieve both adaptability and control [2], [3].

Artificial intelligence (AI) is a major factor in the emerging hybrid scenarios that seek to improve performance through new means. With the help of AI, project managers can be more effective in decision-making when it comes to creating plans, anticipating risks, and allocating resources [4]–[6]. The support

provided by AI-based analytics also includes prediction, real-time monitoring, and performance evaluation across numerous project knowledge areas [7], [8]. However, present-day AI applications are often developed in isolation, which reduces their potential impact when applied separately [9].

A potential avenue for improvement is the integration of these different AI applications into a single framework. To achieve this, complex project decisions need to be supported by structured methods such as multi-criteria decision analysis (MCDA). These models not only provide the required support but are widely trusted for project selection and evaluation. Among them, the weighted sum model (WSM) is identified as the most transparent and easiest to apply [10], [11]. Moreover, when combined with AI-generated indicators, WSM becomes a practical instrument for prioritizing the most relevant success factors in hybrid PM, ensuring that evaluations are systematic and decision-making adaptive.

Despite this potential, most of the existing works have concentrated either on radical aspects of AI implementation or on the hybrid nature of projects. So far, there is no complete model that effectively brings together AI analytics and MCDA methods such as WSM. Only a few studies explicitly examine the importance of this integration for project features such as schedule, resource, and risk management. This research therefore aims to address the following questions: what are the main success factors repeatedly identified in recent studies that affect the performance of traditional, Agile, and hybrid methods? how can WSM be utilized for the organization and ranking of factors for a more efficient hybrid PM framework? furthermore, what is the impact of AI in decision-making when paired with WSM in hybrid PM settings?

This paper's contribution can be explained in terms of the following points: the first is that it presents a systematic review of articles on AI-hybrid project management model (HPMM) published after 2019 and, along with the exposure of numerous possibilities, it also identifies several remaining gaps. The second introduces WSM as a user-friendly tool for weighting and ranking criteria in hybrid PM. The third constructs an AI-WSM-Hybrid framework, leveraging the power of AI for intelligent data processing and multi-criteria decision support. Finally, it presents a comparative evaluation that highlights improvements in several aspects such as schedule adherence, resource allocation, and decision-making effectiveness.

To guide the reader, the rest of the paper is briefly introduced as follows: section 2 presents the background of the study. Section 3 reviews the related work. Section 4 outlines the proposed AI-WSM-Hybrid framework and the applied methods. Section 5 delivers the findings, interpretation, and limitations. Finally, section 6 provides the conclusions, practical implications, and suggestions for future research.

2. BACKGROUND

PM has evolved significantly within the past few years. Traditional approaches, such as the Waterfall approach, are still effective if the requirements are stable, and the processes are predictable. However, they often fail to adapt to today's rapidly changing environments [11]. As a result, many companies have adopted Agile methods. The latter are characterized by flexibility, teamwork, and better stakeholder interaction—qualities that enable the success of dynamic projects. Nevertheless, the sole application of Agile methods does not guarantee success in complex or large-scale projects that are highly regulated [12], [13].

HPM has thus emerged as a solution to address such problems. Through a fusion of PM and adaptive practices, HPM is able to impart both robustness and flexibility [14], [15]. Recent studies show that AI-supported hybrid models are gaining increasing relevance in modern PM practices and are chosen for the management of the aforementioned types of industries such as information technology (IT), construction, and healthcare, which confront a situation of uncertainty and have to comply with the regulations simultaneously [2], [3].

On top of this, PM is also impacted by the implementation of AI. Some of the activities that AI tools carry out for a project include risk forecasting, resource optimization, and progress monitoring, all in real time [16]. When integrated with HPM, AI contributes predictive insights and supports adaptive decision-making, which are often beyond the capabilities of traditional or purely Agile approaches [6].

Moreover, the intricacies of large-scale projects may necessitate the use of structured procedures for decision-making. MCDA is presented as the means that can assist managers in weighing alternatives and ranking objectives. Among the MCDA techniques, the WSM is the most favoured because of its simplicity and straightforwardness [9]. When AI-generated indicators are incorporated into WSM, it becomes an effective instrument for rating the factors of success, balancing the opposing forces, and thus, adaptive decision-making becomes feasible in project knowledge areas [17].

3. RELATED WORK

Recently, the integration of AI and HPM has become a major research focus, as it addresses increasing complexity, volatility, and rapid change in project environments. Although traditional methods such as Waterfall remain effective in stable and regulated environments, they lack the necessary flexibility.

Agile, on the other hand, enhances adaptability and stakeholder involvement, but it is less suitable for complex or highly regulated projects. Hybrid approaches, which combine both paradigms, have proven more effective in dealing with uncertainty and are widely adopted in sectors such as IT, construction, and healthcare [18], [19]. However, most hybrid models remain at a conceptual stage and lack real-time decision-support capabilities.

AI is increasingly recognized as a key driver of innovation in PM, improving resource planning, risk prediction, and scheduling [12], [20], [21]. However, AI applications are often developed in isolation and are rarely integrated with structured decision-making frameworks. In this context, MCDA, particularly the WSM, provides a simple and transparent approach for ranking project success factors and supporting decision-making [9], [10].

Studies ranging from cost prediction [22] to the integration of AI with building information modelling (BIM) for decision-making [23] confirm the effectiveness of AI in targeted applications. However, these approaches often remain fragmented, lacking unified frameworks that integrate AI analytics with MCDA methods within the HPM context. In addition, HPM research highlights low organizational maturity and limited integration of advanced analytical decision-making processes [24].

Furthermore, recent methodological reviews emphasize the growing adoption of data-driven, hybrid, and interdisciplinary approaches that combine Agile principles, decision-support tools, and digital collaboration environments [25]–[28]. A comparative synthesis of these studies is presented in Table 1, which summarizes their domains, methodologies, findings, and limitations, and highlights the research gaps addressed by the proposed AI–HPMM framework.

Table 1. Comparative summary of recent studies on AI and HPM (2019–2025)

Ref.	Domain/context	Data source	Methodology	Key results	Reported limitations
Ali <i>et al.</i> [22] (2022).	Construction (cost estimation)	Historical project data	ML (random forest and XGBoost)	Improved cost prediction accuracy; reduced financial risks.	Focused only on cost; lacks integration with decision-support models.
Uddin <i>et al.</i> [6] (2022).	General project analytics	Industry case study	ML+network analytics	Improved project time/cost/quality predictions.	Limited scalability; no integration with hybrid PM frameworks.
Uddin <i>et al.</i> [19] (2024).	Large-scale infrastructure	Case data	ML+optimization	12–18% delay reduction in schedules.	Focuses only on scheduling; no holistic PM framework.
Reiff and Schlegel [14] (2022).	Hybrid PM review	Scientific literature review (SLR)	Systematic review	Identified hybrid PM challenges and gaps.	No practical AI integration; conceptual only.
Székely <i>et al.</i> [18] (2025).	Hybrid PM (scoping)	Literature synthesis	Scoping review	Hybrid models increasingly adopted in regulated sectors.	Mostly conceptual; no empirical validation.
Salimimoghdam <i>et al.</i> [7] (2025).	AI in PM	100+ papers (2019–2024)	SLR	Mapped AI opportunities, enablers, and barriers.	Lacks unified decision-support integration.
Müller <i>et al.</i> [8] (2024).	AI and PM (empirical)	Surveys and cases	Empirical analysis	Evidence of AI improving risk, cost, and resource control.	Focused on adoption barriers; no integrated MCDA link.
Pacagnella and Silva [24] (2023).	Agile adoption	Literature	Review	Agile improves stakeholder engagement.	No comparative link with hybrid+AI.
Moreno <i>et al.</i> [29] (2024).	Pre-construction (Agile)	Construction	Case analysis	Agile improves stakeholder feedback.	Weak on cost/risk control; no AI component.
Nejad <i>et al.</i> [21] (2025).	Infrastructure (bridge)	Case study	Hybrid MCDA tools	Better constructability review.	Focused on single case; limited generalization.

This study addresses the identified gap by introducing the AI–WSM–HPMM framework, which combines AI capabilities with a clear, structured decision-making approach. The model enhances decision-making efficiency and supports organizational adaptability by continuously identifying and prioritizing key success factors.

Recent methodological advances reinforce the foundation of AI-driven decision-support systems, particularly in terms of interpretability, feature selection, and hybrid learning. Explainable AI emphasizes the need for transparency and interpretability [30], [31] while ensemble and hybrid learning methods improve robustness and prediction accuracy [32], [33]. Moreover, hybrid decision-support systems that integrate AI with MCDA techniques (e.g., WSM, analytic hierarchy process (AHP), technique for order preference by similarity to ideal solution (TOPSIS)) enhance consistency and interpretability [34]. Advances in AI-based predictive analytics further improve responsiveness and foresight in complex project environments [35]. Together, these developments support the transparency, robustness, and theoretical validity of the proposed AI–HPMM framework.

4. PROPOSED METHOD

This section describes the methods used in the present research, which combine the classification of the SLR, the application of the WSM, and the creation of an AI-HPMM. The workflow adhered to the updated preferred reporting items for systematic reviews and meta-analyses (PRISMA) 2020 criteria to uphold both openness and replicability.

4.1. Research design

This research combines a SLR with a conceptual modelling approach. The SLR follows PRISMA 2020 guidelines to be more transparent and reproducible [24]. The review findings have been utilized to recognize the success factors of projects, from which the most important issues have been identified using the WSM [9]. Afterward, these results were then combined with the newly introduced AI-WSM-HPMM [18].

4.2. Systematic literature review procedure

The literature review was conducted using Scopus, Web of Science, IEEE Xplore, and ScienceDirect. A total of 452 studies (2019–2025) were identified using keywords such as hybrid PM, AI, machine learning, WSM, and success factors [23], [25]. After removing duplicates (102), 230 records remained. Title and abstract screening, followed by full-text assessment, resulted in 37 peer-reviewed journal articles being selected as the final dataset [18], [20]. Non-English papers and those not related to AI, PM, or decision models were excluded. The review process follows PRISMA 2020 guidelines and is illustrated in Figure 1, which outlines the stages of identification, screening, eligibility, and inclusion.

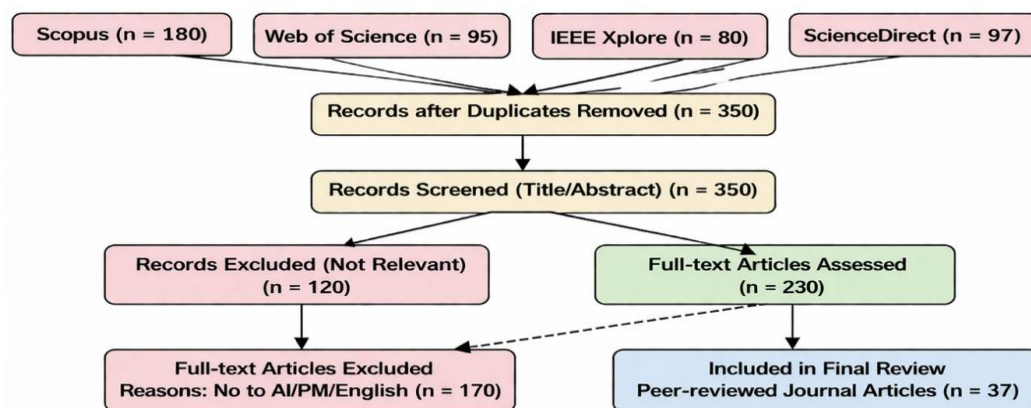


Figure 1. PRISMA flow diagram for the SLR (2019–2025)

4.3. Success factor extraction and categorization

Out of the 37 articles selected for the review, project success factors that frequently appeared in the literature were identified and manually coded. These factors were then mapped to the ten project management body of knowledge (PMBOK) performance domains (7th edition). This process ensures alignment with established PM standards and transforms fragmented findings into a structured decision-support framework. Supplier monitoring was identified as an important factor, although it is often underemphasized in the literature. The importance of reliable suppliers, efficient procurement processes, and reduced supply chain risks has become more evident in hybrid project environments. At the same time, AI-based approaches to cost and strategic planning help reduce operational costs and improve the prediction of potential disruptions [36], [37].

Communication and collaboration were identified as key cross-cutting domains influencing multiple aspects of project success. Effective communication enhances transparency, builds trust, and aligns stakeholders. Recent studies show that AI tools such as chatbots and virtual assistants support communication by automating information exchange and facilitating coordination in distributed teams [38].

4.4. Weighted sum model

The WSM is one of the most commonly used MCDA methods. It assigns weights to evaluation criteria and aggregates the weighted scores to compute the overall performance value for each alternative. The overall score is calculated as:

$$\text{WSM total score} = \sum_{i=1}^n (w_i \times s_i).$$

Where s_i is the score assigned to the methodology for criterion i , w_i is the weight of criterion i , and n is the total number of criteria (ten in this study). The weights were determined using a two-step approach based on 37 peer-reviewed articles (2019–2025). First, frequency analysis was used to measure how often each criterion appeared in the literature. Second, content analysis was conducted to assess contextual importance based on thematic relevance and keyword prominence. As a result, factors such as flexibility, planning and deadlines, and risk management received the highest weights (0.13), whereas supplier monitoring and customer satisfaction were assigned lower weights (0.06) due to their limited emphasis in the literature.

These weights reflect trends in current research rather than absolute practical importance. Table 2 presents the weighted criteria and their rationale, combining insights from PMBOK (7th edition) and recent AI-enabled PM studies.

Table 2. Weighted evaluation criteria and rationale for Agile, Waterfall, and HPM models

Criterion	Weight	Rationale
Flexibility	0.13	Highest influence on responsiveness in dynamic environments; enables adaptation to changing stakeholder demands [18], [26].
Planning and deadlines	0.13	Critical driver of delivery success and milestone alignment; delays remain the most common cause of project failure [11], [27].
Risk identification and mitigation	0.13	Prevents cost/time overruns through early detection; increasingly enhanced by AI-driven predictive models [4], [39].
Resource allocation	0.12	Optimizes cost efficiency and productivity; AI enables dynamic allocation that reduces under/overutilization [5], [40].
Budget accuracy and cost control	0.12	Ensures financial sustainability and trust; predictive AI models improve accuracy in cost estimation and forecasting [36], [41].
Communication and collaboration	0.09	Supports transparency, decision-making, and distributed teamwork; boosted by AI tools such as chatbots and collaborative dashboards [38].
Deliverable optimization	0.08	Ensures high-quality outputs through defect prevention and iterative improvements; enhanced with AI-based QA [15], [40].
Requirement management	0.08	Aligns evolving needs with delivered outputs; critical for maintaining scope clarity and functionality [25], [28].
Supplier monitoring	0.06	Procurement performance impacts cost and schedule; AI improves agility in vendor monitoring and risk assessment [37], [42].
Customer satisfaction	0.06	Reflects stakeholder value and project reputation; strong driver for iterative improvement and ROI [24], [29].

The weighted criteria served as the basis for the assessment of the three PM models, namely Agile, Waterfall, and AI-HPMM. The 1–10 scores attributed to each method for every criterion were derived through a structured qualitative synthesis of performance evidence reported in studies published after 2019, using a literature-based scoring rubric. To ensure clarity and transparency, the scoring method was kept simple. Scores of 9–10 indicate strong and consistent support across multiple empirical or review studies; scores of 7–8 indicate moderate support with recurrent but less consistent evidence; scores of 5–6 indicate limited or context-dependent support; and scores below 5 indicate weak support or clear limitations reported in the literature. Accordingly, the assigned scores should be interpreted as literature-informed comparative ratings rather than direct statistical averages.

4.5. Comparative evaluation using the weighted sum model

To evaluate the performance of Agile, Waterfall, and AI-HPMM methodologies, the WSM was applied across ten predetermined criteria. For each criterion, the methods were scored on a 1–10 scale, and the corresponding weighted scores were then calculated. The main objective of this comparison is to highlight the added value of AI within the conventional PM landscape.

Table 3 results show a numerical comparison between Agile, Waterfall, and AI-HPMM over ten different aspects. Given the iterative cycles and responsiveness to stakeholder feedback that characterize Agile, it scores very high in flexibility (9/10), whereas Waterfall is scored low (5/10) due to its rigid, sequential structure [2], [26]. Both Waterfall and AI-HPMM score 9/10 in planning based on structured scheduling and AI-based forecasting, respectively, while Agile (7/10) is focused on short-term sprint planning [6], [11], [19], [27], [43]. When it comes to risk management, AI-HPMM has the highest score (9/10) because it can detect and mitigate risks in real time, unlike Agile (7/10) and Waterfall (6/10), which rely more on reactive approaches [12], [16].

Table 3. Comparative WSM scores for Agile, Waterfall, and AI-enhanced HPM models

Criterion	Weight	Agile (score)	Weighted Agile	Waterfall (score)	Weighted Waterfall	AI-HPMM (score)	Weighted hybrid
Flexibility	0.13	9	1.17	5	0.65	9	1.17
Planning and deadlines	0.13	7	0.91	9	1.17	9	1.17
Risk identification and mitig	0.13	7	0.91	6	0.78	9	1.17
Resource allocation	0.12	8	0.96	7	0.84	9	1.08
Budget and cost control	0.12	6	0.72	8	0.96	9	1.08
Communication and collaboration	0.09	9	0.81	6	0.54	9	0.81
Deliverable optimization	0.08	8	0.64	7	0.56	9	0.72
Requirement management	0.08	8	0.64	7	0.56	9	0.72
Supplier monitoring	0.06	6	0.36	8	0.48	9	0.54
Customer satisfaction	0.06	9	0.54	6	0.36	10	0.60
Total score (/10)	1.00	—	7.66	—	7.90	—	9.96

In AI-HPMM, resource allocation is significantly enhanced (9/10) through intelligent optimization, outperforming Agile (8/10) and Waterfall (7/10) [5], [40]. Similarly, cost control is improved through predictive analytics in AI-HPMM (9/10), compared with Waterfall (8/10) and Agile (6/10) [8], [36], [41].

In terms of communication, both Agile and AI-HPMM score 9/10 due to continuous stakeholder interaction, with AI-HPMM additionally supported by AI-based tools such as chatbots and collaborative platforms [2], [7], [24], [38]. Deliverable quality is highest in AI-HPMM (9/10) due to predictive validation, compared with Agile (8/10) and Waterfall (7/10) [2], [6], [15], [20].

Requirement management follows a similar pattern, with AI-HPMM (9/10) using AI-based analysis for dynamic updates, outperforming Agile (8/10) and Waterfall (7/10) [2], [12], [24], [28]. For supplier monitoring, AI-HPMM (9/10) also benefits from predictive tracking, exceeding Waterfall (8/10) and Agile (6/10) [14], [17], [37], [42].

Customer satisfaction is highest for AI-HPMM (10/10) due to real-time feedback analytics, followed by Agile (9/10) and Waterfall (6/10) [2], [6], [12], [29]. In summary, AI-HPMM achieves the highest total weighted score (9.96/10), significantly outperforming Agile (7.66/10) and Waterfall (7.90/10). This demonstrates its ability to integrate flexibility, structured planning, and data-driven decision-making within a single framework.

Table 4 comparison of AI-powered elements shows that different tools improve PM in various ways. For example, AI-align and AI-allocator facilitate automation, enhance predictive capabilities, and provide real-time feedback. Altogether, they highlight how AI, as a set of interconnected components, can form the foundation of a unified hybrid model, referred to as the AI-HPMM framework. Section 4.6 explains how the interaction between the AI and WSM layers provides predictive control and decision transparency.

The incorporation of AI modules (AI-planner, AI-risks, AI-chatbots, AI-metrics, and AI-allocator) corresponds to PMBOK process groups (planning, risk, communication, monitoring, and resources). These modules represent key areas where AI delivers significant impact, based on recent research findings [7], [8], [15], [38], through predictive feedback, data-driven analytics, and improved stakeholder engagement.

WSM was selected as the multi-criteria method due to its simplicity, clarity, and ability to handle quantifiable criteria. In contrast, AHP, TOPSIS, and PROMETHEE are more complex and do not necessarily provide better interpretability. Previous studies [9], [10], [17] show that WSM delivers reliable and interpretable results, making it suitable for AI-supported hybrid decision-making.

4.6. Development of the artificial intelligence-enhanced hybrid project management model framework

Building on the systematic literature review, WSM-based evaluation, and AI component analysis, this paper introduces the AI-WSM-HPMM framework. It addresses two major shortcomings of current methods: the lack of real-time adaptability in traditional and hybrid models, and the limited transparency of AI-based decision-making.

The proposed framework follows a dual-layer architecture. The AI layer employs machine learning, natural language processing (NLP), and optimization methods to produce predictive indicators for scheduling, risk, cost, and resource management, thereby facilitating adaptability throughout the project lifecycle [6], [12], [19], [37]. The WSM-based decision layer combines these indicators using weighted multi-criteria logic, ensuring that decisions are both data-driven and transparent. Unlike black-box AI systems, this integration enables decision-making to be traceable and explainable [9], [10].

Figure 2 shows a process-oriented perspective of the framework, structured into the phases planning, Agile execution, and monitoring and optimization. Each phase incorporates AI components such as AI-planner, NLP-AI, and AI-chatbots to support execution cycles while maintaining alignment with project goals.

Table 4. Integration of AI modules in HPM: functions and comparative benefits

Component	Functionality (clear description)	AI value added vs Agile and Waterfall
AI-align (integration)	Automatically integrates new stakeholder requirements and updates dependencies and deliverables in real time.	More than Waterfall: avoids costly late-stage changes. More than Agile: automates requirement integration at scale [12], [38].
AI-planner (schedule)	Builds and adjusts schedules dynamically using team capacity, task dependencies, and real-time performance data.	More than Waterfall: prevents static schedules. More than Agile: uses ML to anticipate delays and adjust proactively [6], [19], [27].
AI-budget (cost)	Applies predictive models to estimate future costs and flag potential overruns before they occur.	More than Waterfall: adds predictive forecasting. More than Agile: enhances accuracy and enables real-time financial tracking [36], [41].
NLP-AI (scope)	Uses NLP to analyze project documents and stakeholder feedback, clarifying ambiguities and updating requirements automatically.	More than Waterfall: improves early clarity. More than Agile: formalizes scope evolution with automated parsing [12], [28].
AI-metrics (quality)	Monitors deliverables against KPIs, detects defects early, and provides corrective recommendations.	More than Waterfall: avoids last-minute QA. More than Agile: enables continuous, objective measurement [15], [28].
AI-feedback (engagement)	Collects and analyzes stakeholder feedback from multiple channels in real time to guide project adjustments.	More than Waterfall enables continuous stakeholder engagement. More than Agile: organizes and prioritizes feedback systematically [12], [29].
AI-sentiment (stakeholders)	Uses emotion and linguistic analysis of emails, surveys, and verbal communication to assess stakeholder satisfaction and detect risks of disengagement.	More than Waterfall uncovers hidden dissatisfaction. More than Agile: quantifies emotions to improve engagement strategies [6], [38].
AI-risks (risk)	Utilizes a combination of real-time and historical data to forecast risks and recommend preventive actions.	More than Waterfall enables earlier risk detection. More than Agile: applies predictive analytics for greater foresight [4], [39].
AI-chatbots (communication)	Automates project updates, answers team queries, and provides relevant information through smart assistants.	More than Waterfall accelerates access to project information. More than Agile: ensures 24/7 availability and supports multilingual communication [38].
AI-supply (procurement)	Evaluates supplier reliability, predicts delivery delays, and supports adaptive vendor selection based on market data.	More than Waterfall introduces flexibility in procurement. More than Agile: improves accuracy in forecasting supply-chain disruptions [37], [42].
AI-allocator (resources)	Intelligently assigns resources based on workload, task complexity, and real-time availability.	More than Waterfall avoids rigid resource allocations. More than Agile: dynamically rebalances resources using live performance data [5], [40].

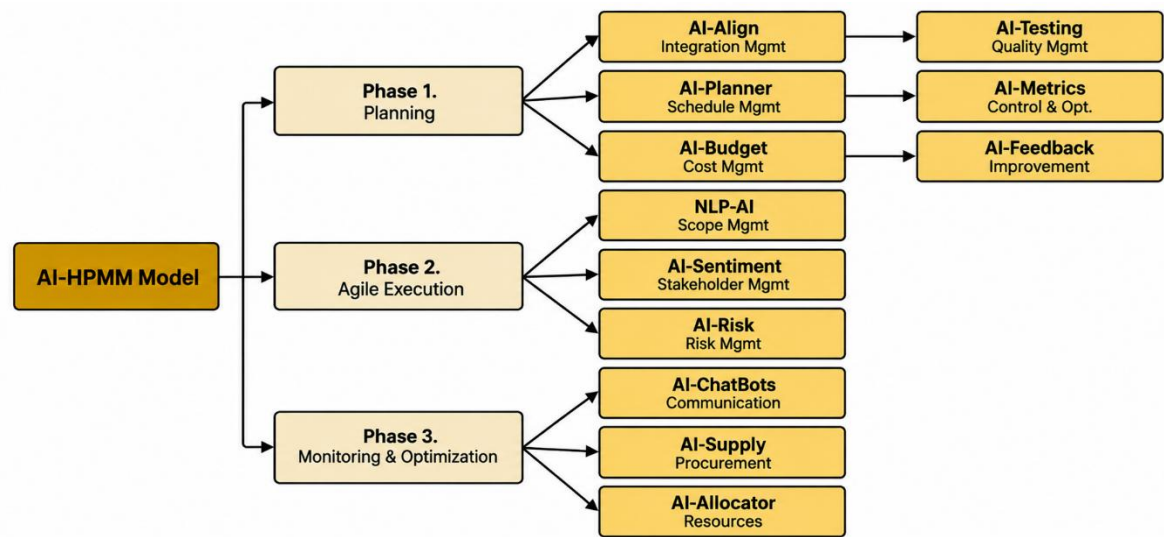


Figure 2. Functional architecture of the AI-HPMM framework

Besides a process-based depiction of operational flow, a system perspective is available to show how the model enables on-the-spot decision-making. As depicted in Figure 3, the design consists of several interconnected AI modules—such as AI-risk, AI-budget, and AI-resources—that deliver their results to the WSM aggregation layer. The combined scores then provide guidance to project managers in choosing the strategies and actions that offer a good compromise between cost, time, quality, and stakeholder expectations. Such architectural modelling also supports the process stage by demonstrating the functional interface between AI-driven insights and manually organized evaluation.

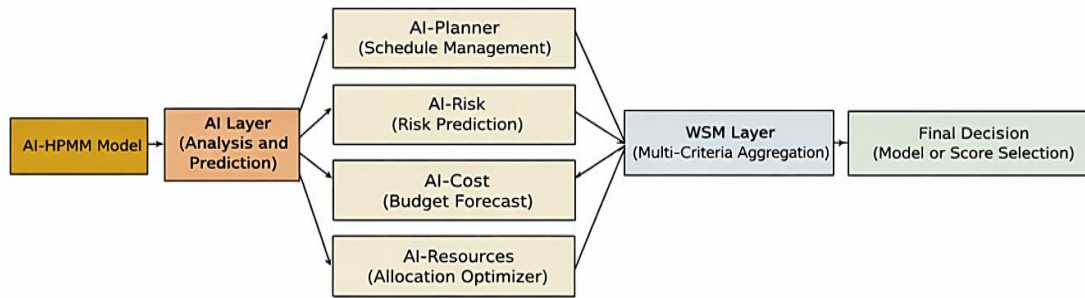


Figure 3. Decision architecture of the AI-HPMM integrating WSM and AI modules

In the AI-HPMM framework, each AI module generates measurable indicators that directly contribute to the WSM. As an example, AI-Align and NLP-AI produce consistency scores (from 0 to 1) that indicate the degree of alignment of stakeholder requirements with current deliverables. AI-Metrics offers quality deviation figures based on the early detection of defects, whereas AI-Allocator calculates resource efficiency using predictive optimization.

All these results are transformed into a common 1–10 scale using standard normalization, so that different metrics can be compared consistently. Each normalized figure is then weighted by its corresponding WSM weight, which indicates its relative significance derived from the literature analysis. The weighted scores thus obtained are added together to obtain the final WSM value — a clear, data-driven representation of the project performance.

Such a coupling procedure ties together AI-generated insights with open, quantitative evaluation, thus providing managers with an understanding of the extent to which each predictive module has led to overall project success. Together, these two perspectives demonstrate how the AI-HPMM framework operationalizes flexibility, predictive control, and structured transparency—key elements required for navigating the complexity of modern project environments. The model provides a robust foundation for transforming HPM into a more intelligent, responsive, and accountable practice.

4.7. Validation approach

Since this research is a literature review rather than a study based on primary data, the validation of the developed AI-HPMM framework is conducted through secondary benchmarking. This method relies on data from peer-reviewed empirical studies comparing AI-HPMM, Agile, and Waterfall across key factors such as time, cost, resource allocation, and decision-making speed.

This non-experimental validation approach provides a consistent and reliable assessment by synthesizing results from multiple studies. Although direct validation was not possible due to the lack of access to real-world AI-enabled project environments, such benchmarking is widely accepted in early-stage model development. Future work will aim to validate the model through pilot testing in real-world settings.

There is substantial evidence from various studies supporting the advantages of AI-based tools in PM. For instance, machine learning-based risk prediction has reduced schedule deviations by up to 15% [4]. Similarly, AI-driven resource optimization improves efficiency by 12–20% through better workload allocation [5], [40]. Decision-making speed has increased by 25–30% due to real-time AI analytics [6], [38], while AI-based cost management improves forecasting accuracy and reduces budget overruns [36], [41].

Taken together, these results provide indirect support for the AI-WSM-HPMM framework. By integrating AI-powered predictive capabilities with a transparent WSM-based decision layer, the model enables faster, more flexible, and traceable decision-making [7], [18]. However, this validation remains limited to secondary data. As noted in previous studies [7], [18], further large-scale empirical validation is required to confirm the model's robustness, refine the framework, and assess its applicability across different domains.

5. RESULTS AND DISCUSSION

5.1. Summary of weighted sum model-based evaluation

The comparison of Agile, Waterfall, and the newly devised AI-HPMM was carried out using the WSM over ten performance criteria. These criteria, derived from a structured literature review and aligned with the PMBOK (7th edition), were already specified and justified in the methodological section (see Table 3).

The data clearly demonstrates the advantage of the AI-HPMM Agile received a total score of 7.66/10, reflecting its main strengths, namely adaptability and team cooperation. Waterfall performed only slightly better, with a score of 7.90/10, primarily due to its strengths in project and budget control. However,

the AI-HPMM significantly outperformed both, achieving a total score of 9.96/10 and delivering a combination of flexibility, predictive control, and structured decision support that was not possible before.

5.2. Analysis by evaluation domain

Agile and AI-HPMM both show high flexibility (9/10), reflecting strong adaptability to changing stakeholder needs, whereas Waterfall remains limited (5/10) due to its rigid structure. In planning, Waterfall and AI-HPMM achieve the highest scores (9/10), with AI-HPMM further enhanced by predictive scheduling, while Agile (7/10) focuses on short-term iterations. Similarly, AI-HPMM leads in risk management (9/10) through real-time prediction, outperforming Agile (7/10) and Waterfall (6/10).

In resource allocation and cost control, AI-HPMM consistently achieves the highest scores (9/10) due to intelligent optimization and predictive analytics, exceeding Agile (8/10; 6/10) and Waterfall (7/10; 8/10). For communication and deliverable quality, Agile and AI-HPMM both score highly (9/10), with AI-HPMM further strengthened by AI-driven tools and predictive validation. Waterfall shows lower performance (6–7/10) due to limited interaction and late-stage testing.

A similar pattern is observed in requirement management and supplier monitoring, where AI-HPMM (9/10) outperforms Agile (8/10; 6/10) and Waterfall (7/10; 8/10) through real-time analysis and predictive tracking. Finally, customer satisfaction is highest in AI-HPMM (10/10), followed by Agile (9/10) and Waterfall (6/10), highlighting the impact of continuous feedback and AI-driven engagement.

5.3. Synthesis of findings

Overall, these results support the idea that AI-HPMM acts as a strong and well-balanced hybrid framework that brings together the three pillars of traditional Waterfall's structured rigor, Agile's flexibility, and AI's intelligence. Unlike typical hybrid approaches, which are mostly theoretical, AI-HPMM presents a practical and transparent model supported by predictive analytics and WSM, thereby ensuring both flexibility and traceability of decisions in complex and regulated environments.

Indeed, these findings are consistent with previous literature showing that AI significantly improves cost estimation, scheduling, and decision-making processes [6], [19], [22]. For example, machine learning techniques such as random forest and XGBoost have been shown to increase cost prediction accuracy [22], while AI-based scheduling approaches reduce delays by 12–18% [6], [19], which is consistent with the 15% improvement reported in this study. Such agreement supports the robustness of the proposed framework across different domains.

However, some discrepancies are observed. Although Agile is generally considered the most effective method for stakeholder engagement [24], [29], the analysis shows that AI-HPMM achieves comparable or higher performance in communication (9/10) and customer satisfaction (10/10). This can be attributed to AI-driven tools such as chatbots and sentiment analysis, which enable continuous and data-driven stakeholder interaction. Earlier comparisons of HPM approaches highlight Waterfall's strengths in planning and supplier monitoring [14]; however, AI-HPMM outperforms these through predictive analytics and vendor monitoring.

AI-HPMM primarily distinguishes itself through three key features: predictive feedback mechanisms enabling early problem detection, automated analytics (e.g., AI-planner, AI-allocator, and AI-budget) that reduce human bias and accelerate decision-making, adaptive learning that improves model accuracy over time. When combined, these elements lead to significant improvements in flexibility, accuracy, and transparency compared with conventional methods.

5.4. Practical implications

From the point of view of management, using the AI-HPMM framework brings several benefits. To start with, it helps avoid project delays by enabling early risk identification and predicting schedule deviations. On the other hand, optimal utilization of resources is achieved through dynamic real-time allocation. Budget management is another area that can be improved, as it can signal potential overruns well in advance. In addition, it promotes greater stakeholder engagement by measuring satisfaction and supporting continuous feedback. Moreover, it helps build transparency and trust through its structured design and interpretable evaluation mechanism. All these features make AI-HPMM an effective decision-support system for managing complex, dynamic, and highly regulated projects.

5.5. Limitations of the study

First, the validation is based on secondary data from peer-reviewed studies (2019–2025), which may introduce bias and limit the generalizability of the results. Secondly, the performance of AI-HPMM depends heavily on the availability of high-quality data. Poor data handling can significantly reduce prediction accuracy [7], [8]. In addition, adoption may be hindered by factors such as organizational resistance, limited technical maturity, and lack of trust in AI technologies [21], [25].

Furthermore, the scalability of the model has not yet been assessed for large-scale or cross-sector projects involving complex interdependencies, large data volumes, or real-time analytics requiring substantial computational resources [6], [7], [19], [38]. In addition, the predictive modules may inherit biases from historical datasets, which could affect decision-making. Therefore, bias detection and explainability mechanisms are necessary to ensure fair and transparent outcomes [30], [32], [35].

Finally, challenges related to infrastructure readiness, cybersecurity, system integration, and implementation costs may arise, particularly for organizations at early stages of digital transformation [8], [16], [21], [37]. However, these challenges do not prevent the use of the model but highlight the importance of context-aware implementation.

6. CONCLUSION

This study introduced the AI-HPMM, designed to address the growing need for intelligent, transparent, and adaptable instruments in PM. By integrating AI components with the WSM, the proposed framework enhances decision-making through a structured, data-driven, and explainable approach. The incorporation of AI modules, including AI-planner, AI-risks, and AI-sentiment, contributes to improved traceability, responsiveness, and interpretability within HPM contexts. Despite these contributions, the study has several limitations. The findings are primarily based on secondary data derived from peer-reviewed literature (2019–2025), which limits empirical generalization. In addition, the scalability of the model across large-scale or cross-sectoral projects has not yet been validated, and its effectiveness may depend on data quality, governance structures, and organizational readiness for AI adoption. Future work will focus on validating the proposed AI-HPMM framework through pilot case studies in real-world environments (e.g., construction or IT), using datasets of multiple projects with key performance and interaction features. A benchmarking analysis against a HPM model without AI will be conducted to assess improvements in cost efficiency, schedule adherence, and risk prediction. Additionally, fairness, bias, and explainability aspects will be evaluated to ensure trustworthy and transparent AI-driven decision-making. Overall, this research contributes to advancing HPM by bridging AI-driven analytics with structured evaluation methods, while also providing a practical foundation for developing more adaptive, interpretable, and intelligent PM systems.

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AUTHOR CONTRIBUTIONS STATEMENT

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- C : **C**onceptualization
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Va : **V**alidation
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D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**ding
- Vi : **V**isualization
Su : **S**upervision
P : **P**roject administration
Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

This study is based on conceptual and analytical methods and does not involve primary data or executable code. The WSM procedure (normalization, weighting, and evaluation) is fully described in Section 4.4 and can be replicated. A public repository with Python scripts and synthetic datasets will be provided in future work to enhance reproducibility.

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